RMUTP **รายงานบทความวิจัย**
(Conference Proceedings)

การประชุมวิชาการเครือข่ายวิศวกรรมไฟฟ้า ครั้งที่ 17
The 17th Electrical Engineering Network 2025

จัดโดย : สมาคมไฟฟ้าและพลังงานไอทริปเปิลอี (ประเทศไทย) (IEEE PES-THAILAND)
สมาคมวิชาการทางวิศวกรรมไฟฟ้า (ประเทศไทย) (EEAAT)
เครือข่ายวิศวกรรมไฟฟ้า (EENET)
มหาวิทยาลัยเทคโนโลยีราชมงคลพระนคร (RMUTP)

EENET 2025

การสร้างนวัตกรรมเทคโนโลยีเพื่อการวิจัย มาพัฒนาท้องถิ่นส่งเสริมเศรษฐกิจชุมชน

Creating innovation technology for research and local development promoting the economy to the community

Conference Topics

- ไฟฟ้ากำลัง Electrical Power (PW)
- อิเล็กทรอนิกส์, วงจร และสื่อสาร Electronics, Circuit and Communicatiion (EC)
- อิเล็กทรอนิกส์กำลัง Power Electronics (PE)
- คอมพิวเตอร์และเทคโนโลยีสารสนเทศ Computer and Information Technology (CP)
- ระบบควบคุมและการวัด Control Systems and Instrumentation (CT)
- ระบบประมวลผลสัญญาณดิจิทัล Digital Signal Processing (DS)
- พลังงานและการอนุรักษ์พลังงาน Energy and Conservation of Energy (ES)
- นวัตกรรมและสิ่งประดิษฐ์ Innovation and Invention (IN)
- งานวิจัยที่เกี่ยวข้องกับวิศวกรรมไฟฟ้า General Electrical Engineering (GN)
- หัวข้อพิเศษทางวิศวกรรมไฟฟ้า Special Session on Electrical Engineering (SS1)
- งานวิจัยด้านการบริหาร การจัดการด้วยขบวนการร่วมกับเทคโนโลยีเพื่อเกิดการพัฒนา (SS2)
- หัวข้อวิจัยที่เกี่ยวข้องกับวิศวกรรม สำหรับนักวิจัยรุ่นเยาว์ ระดับมัธยม ปวช. และ ปวส. (SS3)

https://ee.eng.rmutp.ac.th/

https://eenet2025.rmutp.ac.th/

28 - 30 พฤษภาคม 2568 ณ เฮอริเทจ แกรนด์ คอนเวนชั่น จังหวัดระนอง

บทความวิจัยสาขา DS ระบบประมวลผลสัญญาณดิจิทัล

Adaptive Sigmoid-Based Low-light Image Enhancement

Thaweesak Trongtirakul[1*] Shiquan Wu[2] and Sos Agaian[3]

[1*]Department of Electrical Engineering, Faculty of Industrial Education, Rajamangala University of Technology Phra Nakhon
[2]Institute of Advanced Displays and Imaging, Henan Academy of Sciences
[3]College of Staten Island and the Graduate Center, City University of New York (CUNY)
E-mail: thaweesak.tr@rmutp.ac.th*

Abstract

Low-light image enhancement encounters major challenges, frequently leading to artifacts such as color distortion and noise amplification. This paper presents a novel sigmoid-based adaptive approach to address these limitations, enhancing visibility and quality in poorly lit images. Our method dynamically modifies pixel values using a sigmoid function customized to local image characteristics. This content-aware processing adjusts to different regions within an image, improving dynamic range while preserving natural hues. Furthermore, we utilize a block-based algorithm in the *HSV* color space to increase local contrast. By operating in *HSV*, we enhance brightness and contrast without compromising color fidelity, a prevalent issue in existing methods. This approach effectively tackles non-uniform illumination, generating enhanced images with natural and realistic colors. Unlike previous methods that often oversaturate or amplify noise, our adaptive sigmoid function offers balanced enhancement, uncovering hidden details while maintaining a natural look. Experiments on the *LOL* dataset showcase our method's superiority over state-of-the-art techniques. Both qualitative and quantitative measures indicate improved shadow detail recovery, noise suppression, and color preservation, areas where traditional methods typically fall short.

Keywords: block-based image enhancement, low-light images, sigmoid-based image enhancement, non-uniform illumination

1. Introduction

Low-light image enhancement remains a critical challenge in computer vision, with applications such as autonomous navigation [1] and surveillance systems [2] to medical imaging [3, 4] and astronomical observation [5]. Images captured under insufficient illumination often suffer from poor visibility, color distortion, and amplified noise, which degrade the performance of computer and robot vision systems compared to well-lit conditions [6]. While existing enhancement methods have made significant progress [7], fundamental limitations persist in balancing detail preservation with noise suppression across diverse illumination scenarios [8].

Traditional Retinex-based approaches decompose images into reflection and illumination components through constrained optimization [9, 10]. The Multi-Scale Retinex (MSR) algorithm lead the direction by applying Gaussian filters at multiple scales to estimate illumination but often introduces halo artifacts near high-contrast edges due to improper scale selection [11, 12].

Recently, trailer-based low-light image enhancement approaches exploited the Retinex theory [13-16]. Fusion-based method for weakly illumination imagery (MF) attempted to combine multi-exposure inputs through reflection and illumination components [13]. While Low-light image enhancement with Semi-Decoupled Decomposition (LADD) method estimated the illumination component by using a Gaussian Total Variation model [14]. The reflection is estimated by jointly estimating its input image and the intermediate illumination. It demonstrates chrominance information. Adaptive Logarithmic Retinex (ALR) method utilizes a parametrized logarithmic model to visual details of visible imagery [15]. Finally, Adaptive Single Low-Light Image Enhancement (ASLLIE) method the logarithmic domain fractional stretching approach to estimate the reflectance component of the image based on the modified Retinex theory [16]. However, these approaches frequently amplify noise in dark regions and struggle with color fidelity preservation, particularly in scenes with non-uniform illumination.

This paper presents a novel low-light image enhancement framework addressing these limitations through two key innovations. First, we develop an adaptive sigmoid-based low-light image enhancement function that dynamically adjust parameters based on the illumination of an image. Second, we introduce a block-based image enhancement that enhances local contrast and preserve chromatic fidelity.

The remainder of this paper details our technical details in Section 2, computer simulation validation in Section 3, and concludes in Section 4.

2. Proposed Method

The proposed method enhances low-light images using a multi-step processing pipeline based on the HSV color model, sigmoid-based contrast enhancement, and adaptive contrast enhancement techniques. The steps involved in the method are as follows:

ALGORITHM 1: Adaptive Sigmoid-based Low-light image Enhancement (ASLE)

Input: Low-light image $I_{i,j,k}^{RGB}$ in RGB format.
Output: Enhanced image $E_{i,j,k}^{RGB}$ in RGB format.

Read the input low-light image, $I_{i,j,k}^{RGB}$.
$I_{i,j,k}^{HSV} \leftarrow HSV\left(I_{i,j,k}^{RGB}\right)$.
$V_{i,j}^{HSV} \leftarrow I_{i,j,k}^{HSV}\ ; k = 3$.
$\bar{V}_{i,j}^{HSV} \leftarrow \frac{V_{i,j}^{HSV} - \min\left(V_{i,j}^{HSV}\right)}{\max\left(V_{i,j}^{HSV}\right) - \min\left(V_{i,j}^{HSV}\right)}$.
Compute $\mu_{\bar{V}_{i,j}^{HSV}}$ and $\mu_{I_{i,j,k}^{RGB}}$.
$\alpha(\beta) \leftarrow \frac{\ln\left(\sigma_{I_{i,j,k}^{RGB}}\right)}{\ln\left(\mu_{\bar{V}_{i,j}^{HSV}} \cdot \sigma_{\bar{V}_{i,j}^{HSV}}\right)} \cdot \beta^{\ln\left(\mu_{\bar{V}_{i,j}^{HSV}} \cdot \sigma_{\bar{V}_{i,j}^{HSV}}\right)}$.
$\bar{\boldsymbol{V}}_{i,j}^{HSV} \leftarrow f\left(V_{i,j}^{HSV}\right)$.
$\boldsymbol{V}_{i,j}^{HSV} \leftarrow \frac{\bar{\boldsymbol{V}}_{i,j}^{HSV}}{\max\left(\bar{\boldsymbol{V}}_{i,j}^{HSV}\right)}$.
$\boldsymbol{I}_{i,j,k}^{HSV} \leftarrow \boldsymbol{V}_{i,j}^{HSV}; k = 3$.
$\boldsymbol{I}_{i,j,k}^{RGB} \leftarrow RGB\left(\boldsymbol{I}_{i,j,k}^{HSV}\right)$.
$\boldsymbol{E}_{i,j,k}^{RGB}(\beta) \leftarrow E\left(\boldsymbol{I}_{i,j,k}^{RGB}\right)$.
$E_{i,j,k}^{RGB} \leftarrow \boldsymbol{E}_{i,j,k}^{RGB}(1.0) + \boldsymbol{E}_{i,j,k}^{RGB}(1.5) - \frac{\boldsymbol{E}_{i,j,k}^{RGB}(1.0) \cdot \boldsymbol{E}_{i,j,k}^{RGB}(1.5)}{\max\left(\boldsymbol{E}_{i,j,k}^{RGB}(1.0), \boldsymbol{E}_{i,j,k}^{RGB}(1.5)\right)}$.

2.1 Adaptive Sigmoid-Based Image Enhancement

Adaptive Sigmoid-Based Image Enhancement aims to enhance image quality by dynamically adjusting pixel values through a sigmoid function designed for local image characteristics, ensuring consistent outcomes across different lighting conditions. This allows for content-aware processing, adapting differently to various regions within a single image. The primary goals include enhancing dynamic range and revealing details in shadows and highlights without an artificial look, preserving natural tones, increasing distinction between features while maintaining image coherence, and preserving or enhancing edges by controlling the function's slope to sharpen boundaries without halo artifacts. It also presents significant challenges in parameter selection, as the effectiveness depends heavily on choosing appropriate values for gain, offset, and scaling factors. Researchers have developed various approaches to automatic parameter estimation using image statistics or machine learning to predict optimal values, but finding the right balance between enhancement strength and natural appearance remains challenging.

Also, over-enhancement can create issues such as halo effects around high-contrast edges, noise amplification in uniform regions, and an artificial appearance. Sophisticated control mechanisms are needed to prevent these artifacts while achieving meaningful enhancement. Additional challenges include computational efficiency for real-time applications and developing objective quality metrics that correlate with subjective perception.

Applications span numerous fields including medical imaging, where diagnostic information must be preserved while improving visibility; satellite and remote sensing, which require enhancement across different scales while managing atmospheric distortion; and consumer photography, which must balance technical enhancement with aesthetic considerations to ensure images remain visually pleasing and natural.

Stevens' power law serves as the foundation of the model of brightness perception. According to this law, the perceived brightness is a power function of the luminance. The perceived brightness, $\psi(I)$, can be written as:

$$\psi(I) = I^{k} \tag{1}$$

where k is an exponent that dictates the rate at which perceived brightness increases as luminance changes. Furthermore, the Weber fraction can be approximated as an exponential function of the log-luminance. The exponent, k, can be modeled as an exponential function given as:

$$k(I) = \alpha\beta^{-\ln(I)} \tag{2}$$

where α and β are parameters that regulate the maximum value and the steepness of $k(I)$, respectively. The transformation function for perceived brightness, $\psi(I)$, is formulated as:

$$\psi(I) = L^{\alpha\beta^{-\ln(I)}} \tag{3}$$

To ensure mean-brightness preservation, the optimal value of α can be determined as:

$$\alpha_{\Phi} = \frac{\ln(\sigma(I))}{\ln(\sigma(I)\mu(I))} \cdot \beta^{\ln(\sigma(I)\mu(I))} \tag{4}$$

where $\sigma(\cdot)$ denotes the standard deviation of an image, $\mu(\cdot)$ represents the mean of an image, and I refers to the normalized luminance. This formulation provides an adaptive image enhancement method that aligns with human visual perception, improving image quality while maintaining a natural brightness distribution as illustrated in Fig. 1.

(a) Given image (b) Sigmoid-enhanced image

Fig. 1 Comparison of original and sigmoid-enhanced images

2.2 Block-Based Image Enhancement

Let $I_{i,j,k}$ be an image of size i, j, k, where i represents the height, j represents the width, and k corresponds to the color component, including red, green, and blue. A transformation matrix B is constructed to reorganize these components for processing as follows:

$$\mathbf{B} = \begin{bmatrix} k_1 & k_2 & k_1 & k_2 & \cdots \\ k_3 & k_4 & k_3 & k_4 & \cdots \\ k_1 & k_2 & k_1 & k_2 & \cdots \\ k_3 & k_4 & k_3 & k_4 & \cdots \end{bmatrix}_{x \times y} \tag{5}$$

By reorganizing all color components, the enhanced color components undergo adaptive histogram equalization applied to the image, $\mathcal{I}_{i,j}$, which serves as input for contrast enhancement. The calculation can be expressed as:

$$\mathcal{J}_{i,j} = f_c\left(\mathcal{I}_{i,j}(\mathbf{B})\right) \tag{6}$$

where $\mathcal{I}_{i,j}(\mathbf{B})$ represents a pattern-structured image array, and $f_c(\cdot)$ is the adaptive histogram equalization function. The enhanced image can be transformed as:

$$E_{i,j,k} = \begin{cases} \mathcal{I}_{i,j}(\mathbf{B}), & \mathbf{B} = k_1 \\ \mathcal{I}_{i,j}(\mathbf{B}), & \mathbf{B} = k_2 \\ \mathcal{I}_{i,j}(\mathbf{B}), & \mathbf{B} = k_3 \end{cases} \tag{7}$$

Fig. 2 presents the enhanced image demonstrated in Fig. 1. The enhancement improves visual clarity and contrast, making finer details more distinguishable.

Fig. 2 Enhanced image of Fig. 1 using the proposed block-based image enhancement

3. Computer Simulation Results

Several hundred test images were taken from the LOL dataset [17] for the comparison of the proposed method with Low-Light Image Enhancement with Semi-Decoupled Decomposition (LSDD) [14], Fusion-based enhancement (MF) [13], Multi-Scale Retinex (MSR) [18], Adaptive Logarithmic Retinex (ALR) [15], and Adaptive Single Low-Light Image Enhancement (ASLLIE) [16]. The state-of-the-art methods were run with the default parameters suggested by the authors.

3.1 Objective Assessment

We utilized Lightness Order Error (LOE), Mean Squared Error (MSE), and Peak Signal-to-Noise Ratio (PSNR) for evaluation. LOE estimates per-pixel lightness ordering errors in the Lab color model between the enhanced image and the low-light image. MSE estimates the deviation from the enhanced image compared with the ground truth image using the mean of the squared intensity errors at all pixels. PSNR estimates the power of the optimal image signal versus the power of the disturbance present in the image's representation.

Based on the results of the LOE, the proposed method results in the lowest LOE for all the images. MF and ASLLIE methods also have comparably low LOE with the remaining. Regarding the MSE performance, the proposed method results in the lowest MSE for all the images with the lowest distortion compared to the reference image. MF also demonstrates competitive MSE values, particularly in the Wok and Closet images. Regarding the PSNR, the proposed method results in the highest PSNR for all the images with the optimal combination of the reduction of the noise and the preservation of the details. MF also results in PSNR comparable to the proposed method, which is closely challenged in *Closet* and *Artwork*.

Table 1 Objective evaluation

Name	Method	LOE (↓)	MSE (↓)	PSNR (↑)
Wok	LSDD	406.1871	2,698.2580	13.8200
	MF	105.6174	775.6870	19.2339
	MSR	281.9548	1,769.5168	15.6523
	ALR	223.2808	1,272.4956	17.0842
	ASLLIE	169.3194	1,060.0726	17.8774
	Proposed	**78.2394**	**599.2004**	**20.3551**
Closet	LSDD	352.5137	2,008.0309	15.1031
	MF	94.6367	527.6742	20.9071
	MSR	196.1180	1,677.5868	15.8840
	ALR	94.2395	680.7467	19.8009
	ASLLIE	199.2656	1,561.8602	16.1944
	Proposed	**75.5468**	**501.1262**	**21.1313**
Artwork	LSDD	349.5060	2,275.2103	14.5606
	MF	96.2218	762.2293	19.3099
	MSR	405.6023	2,351.4322	14.4175
	ALR	155.1539	751.8023	19.3698
	ASLLIE	412.8974	2,455.2964	14.2298
	Proposed	**88.7824**	**723.5868**	**19.5359**

3.2 Subjective Assessment

Although an image holds more quantitative measures regarding other images, its subjective image quality is not necessarily correspondingly higher. Because of this, the following section contains examples of enhanced images for the subjective assessment of their image qualities as well as the comparison of the characteristics of the new approach with the traditional approach.

Fig. 3 demonstrates the enhanced images named *Wok*, *Closet*, and *Artwork* from the LOL database. Based on the visual assessment, LSDD and MF methods provide moderate brightness enhancement but lack contrast in shadowed areas. MSR illustrates good contrast, however, it generates a halo artifact. ALR method results in over-enhancement with unnatural brightness shifts, leading to possible loss of fine details and color distortion. ASLLIE improves visibility but introduces a slightly washed-out appearance. On the other hand, the proposed method achieves a well-balanced enhancement, maintaining natural colors, appropriate contrast, and clear details without excessive brightness amplification.

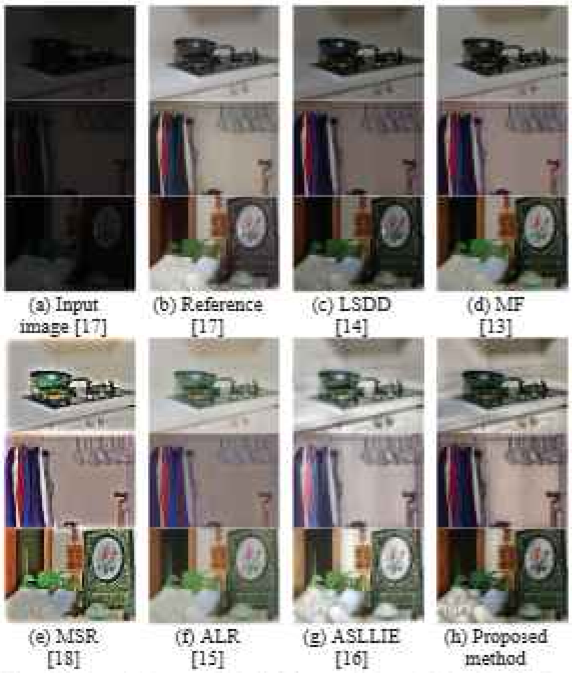

Fig. 3 Enhanced images of *Wok*, *Closet*, and *Artwork* from the LOL database

4. Conclusion

In this study, we have addressed the challenges of non-uniform illumination in low-light imagery. Our approach involves transforming an input image into the *HSV* color-space and applying an image-dependent sigmoid-based image enhancement function. By adaptively adjusting the α and β parameters, we fuse the enhanced imaging components to normalized brightness and information. Furthermore, we visualize the contrast of the color image by performing local image enhancement on a pattern-structured image array. This technique significantly enhances the visual quality, effectively preserving both contrast and brightness, simultaneously.

Comparative evaluations against state-of-the-art methods demonstrate that our introduced framework achieves visually pleasing intrinsic components and outperforms competitive methods regarding subjective observations and objective image quality assessments. The proposed method exhibits adaptability in enhancing images with non-uniform illumination, resulting in natural-looking outputs.

References

[1] R. Sivapriyan *et at.*, "Low Light, Blurred Image Enhancement and Segmentation of Objects for Autonomous Navigation of Vehicles," in *2024 3rd International Conference for Advancement in Technology (ICONAT)*, 6-8 Sept. 2024, pp. 1-8.

[2] S. Ai, and J. Kwon, "Extreme Low-Light Image Enhancement for Surveillance Cameras Using Attention U-Net," *Sensors*, vol. 20, no. 2, doi: 10.3390/s20020495.

[3] T. O. Takpor *et al.*, "Development of a Low-Intensity Light Imaging Probe for Childbirth Cervical Dilation Image Acquisition," *IEEE Access*, vol. 11, pp. 86149-86164, 2023.

[4] A. Oulefki *et al.*, "Enhancing Intubation Accuracy: Advanced Tracheal Segmentation Techniques In Video Endoscopy," in *2024 IEEE International Conference on Image Processing (ICIP)*, 27-30 Oct. 2024, pp.2833-2838.

[5] Y. Liang *et al.*, "Stray Light Correction and Enhancement of Nocturnal Low-Light Image of Early-Morning-Orbiting Fengyun-3E Satellite," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 62, pp. 1-13, 2024.

[6] T. Trongtirakul, and S. Agaian, "New Retinex Model-Based Infrared Image Enhancement," in *Proc.SPIE Commercial Sensing and Defense*, 2023, vol. 12526, p. 1252606, doi: 10.1117/12.2661334.

[7] W. Wang *et al.*, "An Experiment-Based Review of Low-Light Image Enhancement Methods," *IEEE Access*, vol. 8, pp. 87884-87917, 2020.

[8] L. He *et al.*, "Detail-Preserving Noise Suppression Post-Processing for Low-Light Image Enhancement," *Displays*, vol. 83, p. 102738.

[9] E. H. Land, and J. J. McCann, "Lightness and Retinex Theory," *Journal Opt. Soc. Am.*, vol. 61, no. 1, pp. 1-11.

[10] E. H. Land, "The Retinex Theory of Color Vision," (in eng), *Sci Am.*, vol. 237, no. 6, pp. 108-28, Dec 1977.

[11] H. Tsutsui *et al.*, "Halo Artifacts Reduction Method for Variational Based Realtime Retinex Image Enhancement," in *Proc. 2012 Asia Pacific Signal and Information Processing Association Annual Summit and Conference*, 3-6 Dec. 2012, pp. 1-6.

[12] C. Liu *et al.*, "Efficient Retinex-Based Framework for Low-Light Image Enhancement without Additional Networks," *IEEE Transactions on Circuits and Systems for Video Technology*, pp. 1-1, 2024.

[13] X. F. *et al.*, "A fusion-based enhancing method for weakly illuminated images," *Signal Processing*, vol. 129, pp. 82-96, 1 December 2016.

[14] S. Hao *et al.*, "Low-Light Image Enhancement With Semi-Decoupled Decomposition," *IEEE Transactions on Multimedia*, vol. 22, no. 12, pp. 3025-3038, 2020.

[15] T. Trongtirakul *et al.*, "Adaptive logarithmic Retinex enhancement for iceberg detection in visible imagery," in *Proc.SPIE*, 2024, vol. 13033, p. 1303302.

[16] T. Trongtirakul, S. S. Agaian, and S. Wu, "Adaptive single low-light image enhancement by fractional stretching in logarithmic domain," *IEEE Access*, vol. 11, pp. 143936-143947, 2023.

[17] C. Wei *et. al*, "Deep retinex decomposition for low-light enhancement," *arXiv preprint arXiv:1808.04560*, 2018.

[18] M. Afifi *et al.*, "Learning Multi-Scale Photo Exposure Correction," in *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 20-25 June 2021, pp. 9153-9163.